ONLINE MUTUAL FUND INVESTMENT: AN ANALYSIS OF INVESTORS' BEHAVIOUR IN SOME SELECTED DISTRICTS OF WEST BENGAL

Abstract

A thesis submitted to Swami Vivekananda University in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy in Management

By

ARNAB KUMAR BISWAS

SCHOOL OF MANAGEMENT
SWAMI VIVEKANANDA UNIVERSITY
BARRACKPORE, KOLKATA - 700121
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Submitted by

ARNAB KUMAR BISWAS
Registration Number: SVU/PhD/SOM/MGMT/009/2021
School of Management
Swami Vivekananda University

Under the Supervision of

DR. ANIRBAN HAZRA
Assistant Professor
School of Management
Swami Vivekananda University

SCHOOL OF MANAGEMENT
SWAMI VIVEKANANDA UNIVERSITY
BARRACKPORE, KOLKATA - 700121
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Chapter 1. Introduction

श्रेयः हि ज्ञानम् इच्छेत् प्रेयः मन्दः योगक्षेमात्।

श्रेयश्च प्रेयश्च मनुष्यमेतः तौ सम्परीत्य त्यजमानः भवति॥

(śreyo hi jñānamicchet preyo mando yogakṣemāt
śreyaśca preyaśca manuṣyametaḥ tau samparītya tyajamāno bhavati)

—The Katha Upanishad

This line from ancient Indian philosophy aptly captures the essence of decision-making: the choice between the short-term and the long-term gain, between what is pleasant and what is good. It reflects that everyone gets the equal opportunity to choose between the short-term benefit (preya) and long-term gains (sreya). This study interprets this principle in the context of digital financial behaviour — where users often must choose between the comfort of traditional investing and the promises of modern, online investment tools (Venkatesh et al., 2012; Davis, 1989).

In context to this study of digital finance, the choice is between the behavioural intention and the final action taken by the individuals. The thesis explores the dynamics of this choice in the adoption of online mutual fund platforms, with a special focus on investors in West Bengal, India.

1.1: Background of the study

In India mutual funds are administered by the Asset Management Companies (AMCs), who merge the funds gathered from multiple investors and invest in different securities like stocks, shares, bonds etc. Another advantage of mutual funds is that they give the users a chance to spread their investments because it minimize the risks of investment for people of different age groups and classes.

While the idea of mutual funds sales has earlier relied heavily on offline media and personal selling by brokers and financial planners. Now the rise of Indian mutual fund market

has begun to lean heavily towards online selling. This change has been constant with other shift that has occurred in the India's financial services sector and has been a shift to online trading, where people can now engage in financial transactions directly, using their smart phones or laptop, and monitor their performance in real time (RBI, 2021; MeitY, 2022).

1.2: Objectives of the Study

The main purpose of this research is to uncover and compare key online mutual fund behaviour intention and usage patterns in West Bengal. The objective is to map the current level of mutual fund adoption in the online context across the countries of the region and discuss further implications of such behaviours for financial inclusion and market evolution.

Specific Objectives:

1. To Demographically Profile Online Mutual Fund Users in West Bengal
2. To Compare Demographic Differences Between Investors and Non-Investors of Online Mutual Fund
3. To Identify Important Factors which Influence Consumer Awareness of Online Mutual Funds
4. To Determine Key Factors Driving the Usage of Online Mutual Funds
5. To Investigate if the Online Mutual Fund Market in West Bengal Aligns with a Specific User Adoption Model

1.3 Research Questions

This research tries to find out numerous key questions that will allow insights into the adoption behaviour of online mutual funds in West Bengal.

1. Who are the users of online mutual funds in West Bengal?
2. What are the demographic and behavioural differences between investors and non-investors of online mutual fund platforms?
3. What factors influence consumer awareness and decision-making regarding online mutual funds?
4. Are there psychological or social factors that affect online mutual fund usage?

5. Does the online mutual fund market in West Bengal align with existing user adoption models?

Through these research questions, this research work aims to provide a comprehensive idea of the factors driving online mutual fund adoption in West Bengal, helping to identify opportunities along with the challenges in the growth of this market.

1.4: Scope of the study

The study focuses to find out the online mutual fund adoption behaviour of the internet using individuals in West Bengal. The specific scopes are limited to the following:

1. Focus on Internet-Using Individuals in West Bengal
2. Examination of Behavioural and Demographic Variables
3. Analysis of Offline vs. Online User Preferences and Decision-Making Processes
4. Investigation of the Role of Financial Literacy, Convenience, and Digital Infrastructure

1.5: Hypothesis

In order to review these factors systematically, the hypotheses have been formulated, each corresponding to a particular aspect of individual characteristics or behaviour.

Table 1.1: Hypothesis

Hypothesis Code	Hypothesis Statement	Type
H1	Age significantly influences online mutual fund adoption.	Demographic Comparison
H2	Gender significantly influences online mutual fund adoption.	Demographic Comparison
H3	Higher education levels increase likelihood of adoption.	Demographic Comparison
H4	Higher income levels increase likelihood of online mutual fund adoption.	Demographic Comparison
H5	Marital status significantly influences online mutual fund adoption.	Demographic Comparison
H6	Greater comfort with technology increases online mutual fund adoption.	Demographic Comparison
H7	Frequent internet use increases likelihood of online mutual fund adoption.	Demographic Comparison
H8	Frequent use of internet banking increases online mutual fund adoption.	Demographic Comparison
H9	Perceived usefulness positively influences behavioural intention to invest.	Factor → Behavioural Intention
H10	Effort expectancy positively influences behavioural intention to invest.	Factor → Behavioural Intention
H11	Social influence positively influences behavioural intention to invest.	Factor → Behavioural Intention
H12	User interface design positively influences behavioural intention to invest.	Factor → Behavioural Intention
H13	Perceived trust positively influences behavioural intention to invest.	Factor → Behavioural Intention
H14	Behavioural intention positively influences actual usage behaviour.	Behavioural → Actual Usage

These are the base of the analysis to find the major differences between user and non-users and to identify the reasons behind the decision of investing via online mutual fund applications.

Chapter 2. Literature Review

2.1 Overview of Mutual Funds and Digital Transition

The new edge concept regarding mutual funds has seen a huge transformation from its traditional beginning to its modernized form of digital presence. Mutual Fund is always a rich and well-structured investment option with low risks from the beginning of 20th century when it started (Pozen & Hamacher, 2011). In the whole world, mutual fund become a very important investment instrument for people for its diversified choices, easy liquidity options and professional management. Even in India, the mutual fund sector commenced in the year 1963 with the formation of the organization Unit Trust of India (UTI) to collect money from households and direct them towards profitable investments (Ramaswami & Namakumari, 2013).

Over the years, the mutual fund landscape has seen a drastic development. Specially in the 1990s, after the liberalization many international players have come into the market to fight with the national players, which helps Indian economy to evolve in long run. With the continuous advancement in to the mutual funds industry, the main idea of mutual funds has witnessed the shift towards the digital edge. As stated, the flourish of internet technology, along with modernised mobile phones, made it possible to invest in mutual funds in online mode.

2.2 Emergence of Online Mutual Funds

Transformation towards the online platforms is not only technical, it is more of a behavioural shift. Online mutual funds, often referred as digital mutual funds, are investment funds that can be bought, controlled and redeemed through online platforms without the necessity of face-to-face contact (Singh & Malhotra, 2004; AMFI, 2023). The online platforms

help in make the investment simpler for the investors. Not only that it also increases the transparency and reduce the transactional costs. With the emerge of online mutual fund platforms, retail investors can now invest in their desire funds very easily and remotely. Onboarding process of these platforms are super easy and very prompt.

Moreover, the adoption of the online platforms makes the users more empowered where they are able to track their own investments, without intermediaries (Nassiry, 2018; Pavlou, 2003). The investors are clearly removing the third-party interference between them and their investments. The accessibility of the funds is also a key for this behavioural transformational, especially for the users in remote areas, when they can now easily keep track and manage their funds from anywhere in the world at any point in time.

2.3 Behavioural Dimensions of Online Mutual Fund Use

The paradigm behavioural change toward online mutual fund platforms is not uniform. There are multiple factors impacting the same. To understand the behavioural model this thesis developed taking references from two famous behavioural models: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2).

2.3.1 Technology Acceptance Model (TAM)

Davis (1989) has developed the TAM, which is widely used to understand the user's behaviour towards the new technology acceptance. The TAM model hightlights that perceived ease of use and perceived usefulness as two of themajor aspects that influence the decision of the users to either adopt or reject an innovation (Davis, 1989; Venkatesh & Davis, 2000). For the mutual fund platforms, higher perceived ease of use multiply the possibilities that investors will accept the technology. This also highlight the need for the simplified process and interactive user interface.

2.3.2 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

UTAUT2 extends TAM by including constructs such as facilitating conditions, social influence, hedonic motivation, and habit. As per the thesis, TAM and UTAUT2 offered strong frameworks to explore the behaviour of the user in accepting online financial services (Venkatesh et al., 2012). This framework is very much reliable for studying behavioural patterns in areas like West Bengal where socio-economic diversity, technological disparities, and cultural hesitation plays crucial role for influencing user behaviour.

2.4 Socio-Economic and Cultural Contexts in Digital Adoption

In India the path of digital transformation is not that much straight. While metro cities show rapid adoption, regions like West Bengal face structural and behavioural barriers. As stated, despite all these efforts the adoption rate is not always equal, especially in semi-urban and rural areas in West Bengal (Chakraborty & Sengupta, 2020; Singh, 2021). Factors such as digital literacy, risk of losing money, digital fraud, socio-cultural preference and overall trust in digital finance influence user behaviour.

These socio-economic factors are critical in determining who adopts digital investment platforms. Younger individuals, higher-income earners, and more digitally literate populations are more inclined toward online mutual funds. The thesis notes, new-generation investors who are more interested to use the new edge technologies are keener to embrace the system also among the respondent it is visible with higher income and education, the likelihood of investing in online mutual fund is increases very rapidly.

Gender also plays a role (Lusardi & Mitchell, 2014). The study observes that Male participants presented slightly higher adoption than the female participants implying perhaps cultural or financial decision-making differences. These findings align with earlier research suggesting that financial risk tolerance and digital comfort vary significantly across demographic lines.

2.5 Trust, Transparency, and Platform Design

Trust remains a fundamental determinant of digital adoption (Gefen, 2000; Kim et al., 2009). As per the thesis, participants who believed that the security measures of the mutual fund platforms were effective and that the platform was reliable reported high usage intention. Perceived risks such as fraud and data breaches demotivate users from totally embracing digital modes. Hence, platforms must provide strong encryption measures, clear privacy policies, and visible certifications to enhance confidence.

User interface design also impacts user adoption (Thong et al., 2002). The thesis highlights that users tended to appreciate the simplicity of the site, lack of sophisticated technology and ease of use. Therefore, User Interface (UI) and Effort Expectancy are not just technical elements but behavioural motivators that shape platform perception and continued usage.

2.6 Gaps in Existing Literature and Study Rationale

While global studies have extensively validated TAM and UTAUT2, there is a scarcity of region-specific studies in emerging economies like India. The thesis asserts that this contextual application contributes to both academic discourse and practice by revealing how these models may require adaptation in regions with cultural, economic, and infrastructural specificities.

The literature also lacks sufficient exploration of the transition from intention to action—a key gap this thesis addresses through regression modelling and behavioural analysis (Ajzen, 1991; Fishbein & Ajzen, 2010). In essence, understanding why users intend to invest is only half the picture; the real insight lies in explaining why they actually do.

This literature review demonstrates the evolution of mutual funds into the digital age, the behavioural complexities of adoption, and the relevance of TAM and UTAUT2 in decoding user intention. It also reveals significant gaps—especially in the Indian regional context—

which justify the research focus. By bridging theoretical models with localized behavioural insights, this thesis contributes a nuanced perspective to fintech adoption studies.

Chapter 3. Research Methodology

3.1 Introduction

This study tries to find out the behavioural dynamics of the users toward the online mutual fund platforms adoption in West Bengal. For understand that, frameworks like TAM and UTAUT 2 are taken as base of the newly developed model. The influence of psychological, demographic and technological factors in the user adoption is studied by comprehensive research which is structured on a fundamentally strong research methodology.

3.2 Research Approach

This research work employs a mixed method approach in which qualitative data like behavioural factors, intention etc. are systematically converted into quantitative values by using a 5-point Likert scale (Creswell & Creswell, 2018). Key behavioural constructs are perceived usefulness, effort expectancy, trust, social influence, and user interface—were measured and analyzed for regression and factor modelling.

3.3 Research Design

In this research cross-sectional design is chosen which is suitable for identifying patterns and correlations among variables (Bryman, 2016). Data were collected through a structured online questionnaire capturing demographic details, technology familiarity, behavioural intent, and investment activity. All items used a 5-point Likert scale.

3.4 Sampling Method and Sample Design

For this thesis, non-probability quota sampling method is used for getting the feedbcak from the respondents (Saunders et al., 2016). Groups were categorized by age, income level, and education background. Google forms is used to collect data. The Form is circulated via WhatsApp groups, social forums, and investment platforms. For ensuring the responses from

both urban and semi-urban areas of West Bengal, districts like—Kolkata, Howrah, North & South 24 Parganas, Hooghly, Nadia, Siliguri, and Burdwan are chosen. The final sample size was 418 respondents, which meets SEM suitability standards.

3.5 Data Collection Tools and Techniques

The main process of collection data for the study is via sharing google form with a structured questionnaire.

Sections included:

1. Demographic Variables
2. Technology Using Habits
3. Behavioural Variables (TAM/UTAUT2)
4. Investment Behaviour (Investor/Non-Investor)

The form was pre-tested for clarity, especially for semi-urban and rural participants.

3.6 Statistical Tools and Analytical Strategy

For this study multiple statistical tools are used. The tools are:

Table 3.1: Analysis Tools and Purpose

Data Analysis Step	Method Used	Purpose
Descriptive Statistics	Summary of Demographic Profiles and Investment Behaviours	To provide an overview of age, gender, marital status, income, education and internet usage habits among respondents.
Inferential Statistics	T-tests, Chi-Square Test	To look at the differences in the means of variables between people who use online mutual fund apps and those who don't.
Reliability Testing	Cronbach's Alpha	To find the hidden structure of the data and figure out what factors have the most impact.
Validity Testing	Exploratory Factor Analysis (EFA)	To uncover the underlying structure of the data and identify key influencing factors.
Model Development	Regression Analysis	To develop the user adoption prediction models two types of regression are performed.
Model Testing	Structural Equation Modelling (SEM)	To test the developed model and its reliability to predict SEM is performed.

The main analysis is revealed by this very method, so this cross-sectional approach is the perfect choice to identify the relationship of factors with online mutual fund investors'

approach. In this study, the data is analysed mostly on IBM SPSS software which is widely used and accepted in statistical analysis. Few analyses are also performed in Microsoft Excel and SmartPLS 4 software is used for SEM testing and validation checking.

3.7 Ethical Considerations

For this study all the respondents are participated voluntary. No personal data were collected. Confidentiality and anonymity were ensured. The study also tries to minimising the environmental pollution and this is also aligned with the digital behaviour towards online mutual funds.

3.8 Limitations of the Methodology

While the quota sampling ensured diversity, the non-probability nature of the method limits generalizability. There is potential for self-reporting bias and sampling bias, but the chosen method remains practical for regional behavioural research under resource constraints.

Chapter 4. Influence of Demographic and Socio-Economic Characteristics on Mutual Fund Adoption

4.1 Introduction

This chapter tests hypotheses related to demographic and socio-economic factors to assess their impact on users' willingness to adopt online mutual fund platforms. It analyses behavioural differences across groups formed based on demographic variables such as age, gender, and marital status. Both descriptive and inferential methods are used to understand significant patterns between investors and non-investors.

4.2 Variables and Statistical Framework

Independent sample t-test and Chi-Square tests are employs among the information collected from the respondents to identify the effect of several demographic, socio-economic and demographic variables towards the likelihood of online mutual fund adoption behaviour. The variables examined are categorized into:

Demographic Factors: Age, marital status, gender

Socio-Economic Factors: Income level, education

Technological Familiarity: Internet usage, Net Banking usage

User Behaviour: Binary

4.3 Descriptive Analysis of Demographics

The descriptive statistics provide an overview of the demographic, socio-economic, and technological characteristics of the sample population.

Table 4.1: Summary Table of Variables (Based on User Behaviour)

Variable	Group	Mean	Standard Deviation	Proportion (%) / Interpretation
User Behaviour		0.62	0.487	
Age	Investors	2.42	1.00	Younger group (primarily age code 2 = 31–45)
	Non-Investors	3.04	0.85	Older group (primarily code 3 = 46–60)
Gender	Investors	–	–	Male: 77.5%, Female: 22.5%
	Non-Investors	–	–	Male: 53.1%, Female: 46.9%
Marital Status	Investors	–	–	Married: 50.8%, Single: 39.9%, Divorced/Widowed: ~9.3%
	Non-Investors	–	–	Married: 48.8%, Single: 46.3%, Divorced/Widowed: ~4.9%
Income Level	Investors	3.31	0.90	Skewed toward higher-income brackets
	Non-Investors	2.47	1.12	Cantered around lower-income brackets
Education Level	Investors	–	–	Postgraduate: 53.9%, Undergraduate: 23.6%, Vocational: 20.2%
	Non-Investors	–	–	Undergraduate: 46.9%, Postgraduate: 33.8%, High School: 19.4%
Internet Usage	Investors	2.48	0.82	Moderate to frequent users (>3 hours/day)
	Non-Investors	1.89	0.66	Less frequent internet use
Banking Habits	Investors	3.98	–	High familiarity (scale 1–5)
	Non-Investors	3.37	–	Moderate familiarity

Source: Authors' calculation from the primary data

4.5 Summary of Results and Hypothesis

Chi-square and t-test results highlighted that multiple variables significantly affect mutual fund adoption (Hair et al., 2019; Field, 2018):

Table 4.2: Summary of Results and Hypothesis

Variable	Test Used	Test Statistic	p-Value	Conclusion	Accepted Hypothesis	Accepted Hypothesis Statement
Age	Chi-Square	39.86	< 0.001	Significant	Accepted	Age significantly influences online mutual fund adoption.
Gender	Chi-Square	8.96	0.003	Significant	Accepted	Gender significantly influences online mutual fund adoption.
Education	Chi-Square	64.53	< 0.001	Significant	Accepted	Higher education levels increase chances of adoption
Income	Chi-Square	63.81	< 0.001	Significant	Accepted	With higher income the likelihood of adoption increases
Marital Status	Chi-Square	4.23	0.237	Not Significant	Rejected	—
Technology Comfort	T-Test	4.47	< 0.001	Significant	Accepted	Greater comfort with technology increases online mutual fund adoption.
Internet Use	T-Test	6.23	< 0.001	Significant	Accepted	Frequent internet use increases likelihood of online mutual fund adoption.
Internet Banking	T-Test	5.40	< 0.001	Significant	Accepted	Frequent use of internet banking increases online mutual fund adoption.

Source: Authors calculation from the primary data

- Age: The adoption rate for younger people is higher.
- Gender: Males are keener to invest online more.
- Income: Income has a positive corelation with adoption
- Education: Higher qualification boosts adoption rate
- Technology Comfort: technological familiarities increase the adoption chances (Venkatesh et al., 2003).
- Internet and Banking Usage: Internet and Net Banking has a strong positive impact in adoption

Though, marital status has not any significant consistent impact on adoption of online mutual funds.

Chapter 5. Core Determinants Shaping User Preferences in Online Mutual Fund Platforms

5.1 Introduction

In previous chapter the study takes about the demographic, socio-economic and technological factors. This section drive deeper into behavioural influences, pointing on the

key motivational and psychological drivers that shape investor behaviour. It emphasizes the statistical extraction and validation of these components that influence investors' user engagement with online mutual fund using Exploratory Factor Analysis (EFA).

5.2 Methodological Overview

The analysis is rooted on structured questionnaire data and processed using IBM SPSS software. The focus is on identifying latent constructs—perceived usefulness, trust, effort expectancy, user interface, and social influence—that form the backbone of users' behavioural intention. These insights aim to help financial entities to design more user-centric investment platforms.

5.3 Descriptive Statistics of User Perception

Table 5.1: Summary of user perceptions towards investment

Key Area	Statement	Mean	SD	Interpretation
Investment Access	The app provides convenient access to a broad range of investments.	4.20	1.78	The app provides convenient access to a broad range of investments (mean = 4.20) with a standard deviation of 1.78.
Portfolio Tracking	I can check my investments very easily	4.14	1.84	I can easily check my portfolio in real-time using the app (mean = 4.14), which indicates user engagement have a standard deviation of 1.84.
Easy Navigation	The app is very easy to navigate for beginners also.	4.60	1.49	The app is easy to navigate, even for beginners (mean = 4.60) with a standard deviation of 1.49. This suggests a strong consensus among users.
User-Friendly Design	The app design makes it simple to use.	4.90	1.33	App design makes it simple to use (mean = 4.90) with a standard deviation of 1.33. This suggests strong agreement among users.
Quick Transactions	I can complete transactions quickly using the app.	4.95	1.28	I can complete transactions quickly using the app (mean = 4.95) with a standard deviation of 1.28. i.e., there is some good relation with transaction speed.
Data Security	I fully trust the app to keep my personal and financial data secure.	4.75	1.65	I trust the app security (mean = 4.75) with some variability (SD = 1.65). Customer support and transparent policy may increase the trust
Educational Resources	The educational tools in app that helps me to take decisions	4.50	1.52	The educational tools given by the app (mean = 4.50) are valued, though varied engagement levels are indicated by the higher standard deviation.
Customizable Features	I can customize features to suit my investment needs.	4.35	1.70	Users like the Customizable features(mean = 4.35) but with notable variability in responses (SD = 1.70).
Alerts and Notifications	Alerts and notifications are timely and useful.	4.80	1.45	Alerts and notifications are seeming to be timely and useful (mean = 4.80) for the users with moderate agreement among users.
Cost Transparency	The App chargers are simple and clear	4.40	1.74	The cost association of the app (mean = 4.40) shows mixed views, with some users finding it unclear.
Community Engagement	Users can share their responsess on the users' community	4.10	1.80	The community engagement features (mean = 4.10) in the app is a potential area for enhancement.

Source: Authors Calculation from Primary Data

5.4 Factor Analysis Procedure

The **Kaiser-Meyer-Olkin (KMO)** and Bartlett's test are usually employs to check if the data is suitable for factor analysis (Tabachnick & Fidell, 2013).

Table 5.2: Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

KMO and Bartlett Test		
KMO measure of Sampling Adequacy.		0.881
Bartlett's Test of Sphericity	Approx. Chi-Square	8966.452
	df	378
	Sig.	0.000

Source: Authors Calculation from Primary Data

The results show, there is sufficient co-relation among the variables for performing factor analysis.

5.5 Total Variance & Rotated Component Matrix

In this study, after performing PCA, with varimax rotation five major factors are received which is explaining over 72% of the total variance. The factors can be identified as:

Perceived Usefulness – The goal-oriented investment tracking
Effort Expectancy – Easy learning and usability
Perceived Trust – Customer support and data security
User Interface – User experience and application design
Social Influence – Peer review and social recommendation

The factors are similar with TAM and UTAUT2 models which indicates the robustness of literature review.

5.6 Interpretation of Extracted Factors

- Perceived Usefulness – The survey participants have stated that they have used online mutual funds so that investors' can easily control their portfolios, they can track their investments also. It will help them to utilise the current market conditions in terms of their investment. This tracking and planning ability on online mutual fund platforms is a key factor for developing the intent to adoption.

- Effort Expectancy - The findings confirmed that users tended to appreciate the simplicity of the site, lack of sophisticated technology, and ease of use (Venkatesh et al., 2012).
- Trust and Security - Participants who trusted that the security measures of online muual fund platforms were effective and also the platform was reliable reported high usage intention.
- User Interface -Interface design emerged as a contributing factor in satisfaction and platform engagement.
- Social Influence - Word-of-mouth influence from friends and family, suggestions from financial consultants, and online financial forums were stated to be the main reasons people joined the platforms.

Finally, the Conclusive Results section summarizes the findings, highlighting the reduced factor structure and discussing how these core factors represent the essential aspects of Behavioural Intention toward online mutual funds (Ajzen, 1991; Lin, 2011).

Chapter 6. Role of Adoption Drivers in Shaping Behavioural Intentions

6.1 Introduction

The previous chapters, emphasis on a detailed exploration of the components influencing user preferences for online mutual fund platforms. This chapter shifts focus toward testing those factors' predictive power on behavioural intention using statistical techniques such as correlation and regression analysis.

6.2 Descriptive Statistics

In this segment, descriptive statistics of six key factors of user perception and behaviour are presented. The result shows, the mean scores for intention to adopt and related factors (ranging from 4.34 to 4.59) indicate high overall agreement among respondents. This result

justifies the theoretical aspect along with the statistical strength of Behavioural Intention of this study.

6.3 Correlation Analysis

Table 6.1: Correlations Table

Variables	PU	EE	SI	UI	PT	BI
Perceived Usefulness (PU)	1	.324**	.189**	.431**	.179**	.443**
Effort Expectancy (EE)	.324**	1	.195**	.287**	.265**	.477**
Social Influence (SI)	.189**	.195**	1	.170**	.339**	.471**
User Interface (UI)	.431**	.287**	.170**	1	.129**	.502**
Perceived Trust (PT)	.179**	.265**	.339**	.129**	1	.499**
Behavioural Intention (BI)	.443**	.477**	.471**	.502**	.499**	1

Source: Authors Calculation. from Primary Data

Also the Pearson correlation value reveals that Behavioural Intention is strongly associated with Effort Expectancy (r = .477), Social Influence (r = .471), Perceived Trust (r = .499), and User Interface (r = .502). Perceived Usefulness (r = .443) also shows moderate influence. The correlation analysis shows that Behavioural Intention is strongly influenced by effort expectancy, social influence, and perceived trust.

6.4 Regression Analysis

A multiple linear regression was employed using the five predictors developed from EFA in Chapter 5.

6.4.2 Model Summary

The R-squared value is presented, indicating the proportion of variance in Behavioural Intention explained by the predictor variables.

Table 6.2: Regression Model Summary

R.	0.762
R Square.	0.581
Adjusted R. Square	0.576
Stand. Error of the Estimate	0.71722
Durbin-Watson	1.784
Skewness	−0.118
Kurtosis	2.764

Source: Authors Calculation. from Primary Data

Here, 58.1% of the variance in behavioural intention is explained by Social Influence, Perceived Usefulness, User Interface, Effort Expectancy and Perceived Trust.

6.4.3 ANOVA Table (Model Significance)

The F-value of 119.39 and $p < 0.001$ indicate the model is highly significant.

6.4.4 Coefficients Table

Table 6.3: Coefficients

Coefficients.							
Model.	Unstandardized Coefficients.		Standardized Coefficients.	t	Sig.	95.0% Confidence Interval for B.	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	-0.694	0.228		-3.037	0.003	-1.143	-0.245
Perceived Usefulness	0.103	0.026	0.144	3.938	0.000	0.052	0.155
Effort Expectancy	0.216	0.035	0.219	6.238	0.000	0.148	0.283
Social Influence	0.275	0.038	0.251	7.300	0.000	0.201	0.349
User Interface	0.279	0.034	0.297	8.242	0.000	0.212	0.345
Perceived Trust	0.224	0.027	0.291	8.357	0.000	0.172	0.277

Source: Authors Calculation. from Primary Data

- Perceived Trust has the strongest influence (β = .291), followed by User Interface (β = .297), Social Influence (β = .251), and Effort Expectancy (β = .219).
- Perceived Usefulness also contributes significantly (β = .144). Based on the performed multiple linear regression analysis… a mathematical equation is formed to express the relationship of the five factors along with Behavioural Intention.

The regression equation is:

$$\textbf{Behavioural Intention} = -0.694 + 0.103(PU) + 0.216(EE) + 0.275(SI) + 0.279(UI) + 0.224(PT)$$

6.5 Residual Analysis

The mean value of the residuals being 0.00000 shows that the model does not exhibit systematic bias. Standardized residuals fall within −3 to +3, indicating no significant outliers and a reliable model with homoscedastic variance.

Chapter 7. From Intention to Action: Understanding the Transition to Users' Investment Behaviour

7.1 Introduction

This chapter represents a comprehensive statistical analysis of user behaviour regarding online mutual fund platforms. It explores whether strong behavioural intention actually results in investment, using logistic regression where User Behaviour is binary (Investor = 1, Non-Investor = 0).

7.2 Correlation Analysis

The correlation analysis provides a much better understanding of these relationships, looking at the strength and direction between these factors in the decision-making process.

7.2.1 Correlation Between Demographics and User Behaviour

Table 7.1: Correlation I

Variable	Age Group	Gender	Education	Income	Internet Hours	Tech Comfort	Banking Frequency	User Behaviour
Age Group	1	.108	–.076	–.171	–.139	–.002	–.104	–.304
Gender	.108	1	–.070	–.029	–.141	–.031	–.098	–.255
Education Level	–.076	–.070	1	.146	.141	.168	.089	.383
Income Level	–.171	–.029	.146	1	.197	.168	.088	.382
Internet Usage (hrs)	–.139	–.141	.141	.197	1	.092	.227	.352
Technology Comfort	–.002	–.031	.168	.168	.092	1	.117	.313
Banking Frequency	–.104	–.098	.089	.088	.227	.117	1	.318
User Behaviour	–.304	–.255	.383	.382	.352	.313	.318	1

Source: Authors Calculation from Primary Data

Correlation results show that User Behaviour is positively associated with Education (r = .383), Income (r = .382), Internet Use (r = .352), Technology Comfort (r = .313), and Banking Frequency (r = .318). Age (r=-.304) and Gender (r = -.255) suggested that older people and females are less interested to adopt. Also, all the correlations are statistically significant at 0.01 level (2-tailed). No correlation is exceeding ±0.7.

7.3.2 Correlation Between Behavioural Intention and User Behaviour

Behavioural Intention shows a very high (A Pearson coefficient of r = 0.668) correlation with users' behaviour. This strong positive relationship reinforces that intention is a powerful predictor of real action.

Table 7.2: Correlation II

Variables	Behavioural Intention	User Behaviour
Behavioural Intention	1	.668**
User Behaviour	.668**	1

Source: Authors Calculation from Primary Data

7.4 Logistic Regression Model

In this study two regression models were developed to predict online investment behaviour:

7.4.1 Model 1 – Demographics and Tech Predictors

Table 7.3: Logistic Regression Coefficients and Statistical Significance

Model Statistic	Value	Interpretation
–2 Log Likelihood	320.126	Indicates strong model fit
Cox & Snell R^2	0.432	Model explains ~ 43.2% of the variance
Nagelkerke R^2	0.587	Adjusted pseudo-R^2; confirms 58.7% explanatory power of the model
Convergence Iteration	6	Model converged successfully
Hosmer and Lemeshow Test (Chi^2)	6.708	Non-significant (p = 0.568) suggests good fit between observed and predicted values.
Significant Predictors	7 of 8	All except Marital Status are statistically significant (p < 0.05).

Source: Authors Calculation from Primary Data

The model explains up to 58.7% of variance in the User Behaviour (dependent variable) (Nagelkerke R^2), and shows high predictive power.

Table 7.4: Logistic Regression Coefficients and Statistical Significance

Variable	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for Exp(B)
Age Group	–0.598	0.148	16.246	1.	0.000	0.550	[0.411, 0.736]
Gender	–1.174	0.303	14.994	1.	0.000	0.309	[0.171, 0.560]
Marital Status	0.026	0.204	0.017	1.	0.898	1.027	[0.688, 1.532]
Education Level	1.109	0.195	32.439	1.	0.000	3.032	[2.070, 4.441]
Income Level	0.669	0.134	24.861	1.	0.000	1.952	[1.501, 2.540]
Internet Hours	0.793	0.192	17.022	1.	0.000	2.210	[1.516, 3.221]
Tech Comfort	0.498	0.116	18.474	1.	0.000	1.645	[1.311, 2.065]
Banking Frequency	0.796	0.190	17.468	1.	0.000	2.216	[1.526, 3.219]
Constant	–6.435	1.165	30.507	1.	0.000	0.002	—

Source: Authors Calculation. from Primary Data

Key results: Education (Exp(B) = 3.032) and Internet Hours (Exp(B) = 2.210) had the strongest positive impact. Age (Exp(B) = 0.550) and Gender (Exp(B) = 0.309) had significant negative effects. Apart from Marital Status all other factrors are statistically significant ($p < 0.05$).

The derived regression equation is:

$$\boldsymbol{logit(p) = -6.435 - 0.598\,(Age) - 1.1174\,(Gender) + 1.109\,(Education\ Level) + 0.669\,(Income\ Level) + 0.793\,(Internet\ Hours) + 0.498\,(Tech\ Comfort) + 0.796\,(Banking\ Frequency)}$$

7.4.2 Model 2 – Behavioural Intention as Predictor

Table 7.5: Behavioural Intention Model Summary

Model. Statistic	Value	Interpretation
Model Statistics	Value	Interpretation
-2 Log Likelihood.	139.632	A lower value indicates a better model fit.
Cox and Snell R^2	0.441	Indicates approximately 44% of variamce
Nagelkerke R^2	0.600	Adjusted pseudo-R^2; confirms 60% explanatory power of the model
Hosmer and Lemeshow Test (Chi-Square)	25.199	significant (p = 0.000314) suggests possible limitation in model fit.

Source: Authors calculation from the primary data

The model explains up to 60% of variance in the dependent variable (Nagelkerke R^2).

Table 7.6: Logistic Regression Coefficients and Statistical Significance

Variable in the Equation.							
		B	SE.	Wald.	Df.	Sig.	Exp. (B)
Step 1a	Behavioural Intention	2.271	0.219	107.674	1	0	9.689
	Constant	-9.041	0.901	100.788	1	0	0

Source: Authors calculation from the primary data

The logistic regression found that Behavioural Intention (B = 2.271, Exp(B) = 9.689) is a powerful and significant standalone predictor (Fishbein & Ajzen, 2010; Taylor & Todd, 1995). For every one-unit increment of Behavioural Intention, the likelihood of investing in online mutual funds increases by 2.271 times.

The regression equation is

$$\boldsymbol{logit}\,(\boldsymbol{p}) = \mathbf{-9.041} + \mathbf{2.271} \times \boldsymbol{Behavioural\ Intention}$$

Chapter 8. Behavioural Drivers of Digital Mutual Fund Investment and the Model

8.1 Introduction

In this chapter study discussed about the findings of the thesis and evaluate the results based on the existing academic literature and practical implications. Anchored in empirical results, it discusses theoretical inferences and the final user behaviour adaption model. The applicability of established frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) is reassessed in the distinct regional setting of West Bengal.

8.2 Empirical Findings and Theoretical Positioning

This research has found that User Interface, Perceived Usefulness, Perceived Trust, Effort Expectancy and Social Influence are the key component that are impacting the online mutual fund adoption. This is found from critically reading the previous published research papers and articles. These models help to understand how socio-economic and cultural differences among users and non-users influence digital investment behaviour. The theoretical

underpinnings of the study were guided by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2).

8.3 Behavioural Intention and Key Predictors

User Interface (r = 0.502) is analysed to be the strongest correlation with behavioural intention, which means that users are choosing platforms looking at the UX designs, which make it a key driver for accepting the online funds. Effort Expectancy (r = 0.477) has also shown a good corelation with the behavioural intention which clearly shows that the easy usecases are the co-driver for the adoption. Social Influence also showed a robust relationship with Behavioural Intention (r = 0.471), echoing empirical findings that peer endorsement and normative pressures strongly shape digital investment choices.

8.4 Socio-Demographic Factors and Adoption

This research also finds out that, socio demographic and technological variables has also some statistically significant impact in predicting the user adoption to online mutual funds (Lusardi & Mitchell, 2011; OECD, 2020). This study shows the users of 31-45 age group with higher educational, income background and used to digital literacy along with technology comfortable are keener to put money on mutual funds in online platforms. Male are also found to be statistically significant for online adoption.

8.5 From Intention to Action

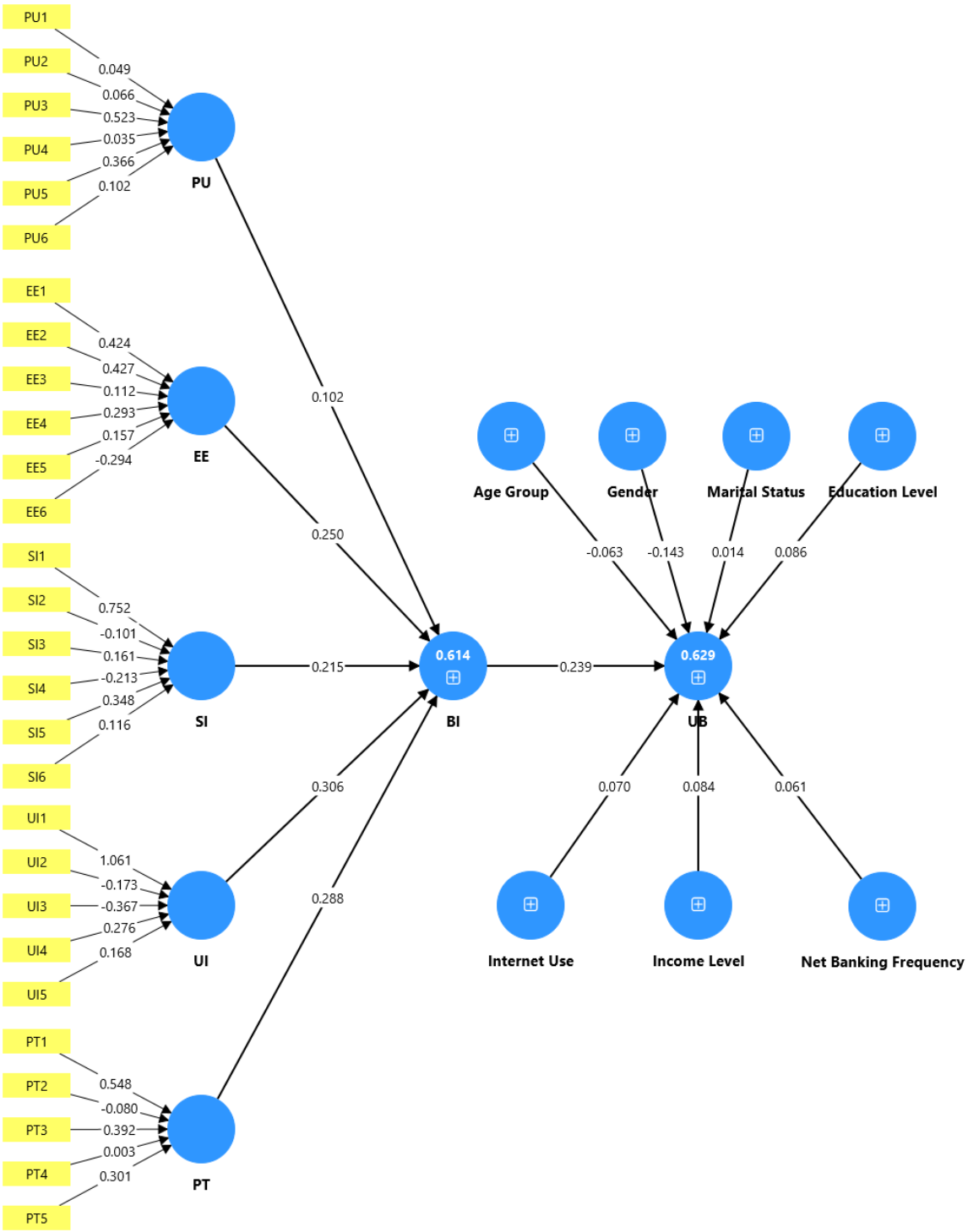
Correlation analysis establishes that behavioural intention (Factor 6) has a strong and statistically significant positive relationship with actual investment behaviour ($r = 0.668$, $p < 0.001$). Logistic regression (Nagelkerke $R^2 = 0.600$) showed that BI, when combined with demographic and technological factors, explained 60% of user behaviour. The high odds ratio (Exp(B) = 9.689) suggests that a one-unit increase in behavioural intention multiplies the odds of investing by nearly ten times.

8.6 Final User Behaviour Adaption Model

The final model encapsulates the complex interrelations between platform-level design features, psychological motivators, demographic factors and actual investment behaviours on online

mutual fund platforms (Venkatesh et al., 2012; Davis, 1989; Pavlou, 2003). With $R^2 = 0.614$ for BI and $R^2 = 0.629$ for UB, the model showed strong predictive power. The Standardized Root Mean Square Residual (SRMR) was 0.042 for the saturated model and 0.059 for the estimated model.

Full Structural Equation Model (FSEM) with Path Coefficients and R^2 Values



Source: Authors calculation from the primary data

Significant path relationships included:

- PT → BI ($\beta = 0.306$, $p = 0.001$)
- EE → BI ($\beta = 0.250$, $p = 0.006$)
- UI → BI ($\beta = 0.288$, $p = 0.002$)
- SI → BI ($\beta = 0.215$, $p = 0.021$)
- BI → UB ($\beta = 0.239$, $p < 0.001$)

Demographic paths are also seen to be statistically significant such as Education → UB ($\beta = 0.086$, $p = 0.005$) and Income → UB ($\beta = 0.084$, $p = 0.015$).

8.7 Implications

From the practicality angle, this model finds that the fintech application developers and mutual fund platforms should targets on making the design attractive and interesting. Tailored outreach based on user demography and digital literacy can bridge the intention-action gap. The study identifies that demographic components such as education level, digital literacy, and income create an important influence on user adoption of online mutual funds.

This study bridges behavioural theory and empirical analysis, validating the relevance of TAM and UTAUT2 in an emerging market context. Effort Expectancy, Social Influence, and Perceived Trust are the strongest predictors of behavioural intention. A significant portion of variance remains unexplained, suggesting the presence of latent psychological, cultural, and infrastructural barriers. By combining interface, trust, and digital education, platforms can meaningfully boost investment adoption in regions like West Bengal.

Chapter 9. Conclusion

9.1 Study Summary

This chapter presents a comprehensive wrap-up of the study, summarizing the main findings, limitations, and suggestions for future work. This study shows that the behavioural intention to invest in online mutual funds is significantly impactful by the factors like age, gender, technology comfort, perceived usefulness, Social Influence, User Interface, Trust, and Effort Expectancy (Ajzen, 1991; Fishbein & Ajzen, 2010). Based on the Tam and UTAUT2 Model, this research tries to develop the online mutual fund user's adoption behavioural model in the context of West Bengal. The study simultaneously offers insights for policy makers and tech development companies along with finance services.

9.2 Summary of the Key Findings

Ten key areas influencing adoption behaviour were outlined:

- Performance Expectancy and Perceived Usefulness: Users value platforms offering financial tools, portfolio tracking, and decision-making ease.
- Effort Expectancy: Simple process flow, user design are and ease of navigation enhance platform adoption.
- Trust and Security: Data protection policy, platform's reliability, brand image of the company are the key aspects of trust. Trust is one of the key contributors for shaping the user behaviour.
- Social Influence: word of mouth and recommendations from the known or family member is strongly affecting investment decisions.
- Facilitating Conditions: A proper customer support and access to required technology is also helps to determine use.
- Price Sensitivity: In online mutual fund, transparency of costing and low-cost barrier sometime attract users.
- Demographics: New generation modern people are most likely to invest in digital format than the older ones.
- Financial Literacy: Kowing about the managing finances information about the product is enhance the adoption.

- Convenience: The ability to invest anytime/anywhere is a core motivator.
- Behavioural Intention: Strong intention is highly correlated with actual usage.

9.3 Limitations of the Work

Several constraints were acknowledged:

1. The study is confined only to the West Bengal region, limiting generalizability.
2. A moderate sample size and use of self-reported data may affect data accuracy.
3. Short data collection duration does not capture behavioural evolution.
4. Exclusion of emotional and psychological variables.
5. Comparison between the platforms and their feature is not taken into consideration.
6. Lack of analysis on regulatory, legal, marketing, and macroeconomic variables.

9.4 Future Scope of the Study

The thesis has done in a comprehensive manner but still there are mores cope of work. So, it suggests future directions:

1. Should have done on a broader geographical area
2. The impact of time can be considered by doing a longitudinal study
3. Integration of behavioural finance theories.
4. Technological factors like encryption and platform transparency.
5. Comparative studies of platform design and user experience.
6. The Government policy and micro economics factors need to studied (RBI, 2021; MeitY, 2022)
7. Use of AI and predictive models for deeper behavioural insights (Zhou et al., 2020; Brynjolfsson & McAfee, 2017)
8. Evaluating financial literacy campaigns.
9. Incorporating human-cantered design and personalization.

10. Investigating emerging technologies like blockchain and 0072obo-advisors.

9.5 Applications and Real-World Use Cases

Based on the study, the thesis suggested some practical applications include:

1. Improved in UI/UX can help to engage more user by improving user's experience
2. Taking the privacy measure and easy communication can increase the trust of users.
3. Social influencers and word of mouth can help in growing user bases.
4. Promoting financial education via tutorials and simulations.
5. Offering cost-efficient products to attract price-sensitive users.
6. Reducing demographic gaps with localized strategies.
7. Continuous innovation and improvement in fintech ecosystems.

9.6 Study Conclusion

This study presents a theoretical advancement and empirical analysis of the factors affecting the adoption of online mutual funds in West Bengal based on the TAM and UTAUT2 model. Behavioural factors like trust, financial literacy, security, and design along with socio-demographical variables such as Age, Gender, Education, Income etc. are encouraging the platforms adoption chances. While highlighting contributions, it also recognizes the need for expanded future research and practical innovations that empower inclusive digital investment behaviours.

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